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AN EFFICIENCY ANALYSIS OF DEFENSE LOGISTICS AGENCY CONTRACT ADMINISTRATION OFFICES

by

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June 1999

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Restructuring within the Department of Defense since 1990 has forced the Defense Contract Management Command (DCMC) to reduce its staffing level from 24,000 to 14,000 employees. The Contract Administration Offices that make up DCMC have reduced from over 100 offices to only 65 offices. This study evaluates the efficiency of these Contract Administration Offices in the wake of this massive reorganization. Statistical analysis determined the most crucial inputs and outputs for use in an efficiency model. Data Envelopment Analysis (DEA) methodology identified efficient and inefficient Contract Administration Offices. Further analysis of the DEA models revealed potential improvement strategies for inefficient offices and suggests uses of the models for future personnel resource forecasting.

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AN EFFICIENCY ANALYSIS OF DEFENSE LOGISTICS AGENCY CONTRACT ADMINISTRATION OFFICES

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ABSTRACT

Restructuring within the Department of Defense since 1990 has forced the Defense Contract Management Command (DCMC) to reduce its staffing level from 24,000 to 14,000 employees. The Contract Administration Offices that make up DCMC have reduced from over 100 offices to only 65 offices. This study evaluates the efficiency of these Contract Administration Offices in the wake of this massive reorganization. Statistical analysis determined the most crucial inputs and outputs for use in an efficiency model. Data Envelopment Analysis (DEA) methodology identified efficient and inefficient Contract Administration Offices. Further analysis of the DEA models revealed potential improvement strategies for inefficient offices and suggests uses of the models for future personnel resource forecasting.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

The Defense Contract Management Command (DCMC) has undergone a significant reorganization in recent years. The number of employees within the command has reduced from 24,000 in 1990 to 14,000 today. It is unknown, however, whether this reorganization resulted in an efficient organization. This study determines the efficiency of the 65 individual Contract Administration Offices located throughout the United States that are assigned to DCMC.

Part of the Defense Logistics Agency, DCMC provides contract management services for most contracts awarded within the Department of Defense; over 350,000 contracts managed at any given time. In order to manage the implementation of these contracts, Contract Administration Offices (CAO) provide continuous contract management services for government program managers overseeing individual manufacturers under contract. CAOs provide support for fact-finding and negotiations between contractors and contracting officers, provide safety and environmental assurance, and evaluate contractor processes and progress, among other duties. Two types of CAOs operate within DCMC: Plant Offices and Area Offices. Area Offices manage contracts within a geographic area. Plant Offices are resident within contractors' plants. Because of the inherent differences in the two CAO types, management has determined that each office type be modeled separately.

Efficiency is a ratio of outputs to inputs. However, difficulties arise in this simple concept when attempting to compare efficiency between units without easily identifiable or countable inputs and outputs or when units have multiple inputs or outputs. The

methodology known as Data Envelopment Analysis or DEA, uses mathematical programming techniques to combine multiple output and input measures to produce a single efficiency score for each organization.

The selection of measures for use in the models is of utmost importance when implementing DEA models. Evidence of a causal relationship between inputs and outputs must be shown though analysis of their associated correlation coefficients. DCMC provided one candidate input measure and eight candidate output measures of which only six output measures are selected for use in the models. Of those six, three fail to show strong evidence of this causal relationship. However, those three measures, the only measures of quality available, are deemed essential to the overall formulation of the DEA models, even though their low correlation coefficient with the input measure weakens the final efficiency results.

Fifteen of the 65 offices are shown to be efficient. Inefficient offices can determine improvement opportunities by examining the measures of efficient offices. To improve, an office must either lower its input, increase output, or both. The resulting scores show that some offices are achieving a greater number of outputs per input compared to other offices. Efficient offices can be used as a benchmark for other offices to emulate.

The DEA models in this study provide a valuable management tool to assist DCMC in determining personnel resource requirements. The great added value with the DEA models is the new visibility over each office's strengths and weaknesses. The rapid

identification of these weaknesses allows management to focus on problems and solve them quickly without a great time investment searching for possible causal factors.

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I. INTRODUCTION

> ...We tend to meet any new situation by reorganizing: a wonderful method
> ... for creating the illusion of progress, while producing ...inefficiency."
>
> -- Petronius Arbiter, 210 BC

A. OVERVIEW

By any measure, the Department of Defense has undergone dramatic reorganization in recent years. Less bureaucracy and smaller organizations are always assumed to be better and in the best interest of the taxpayers. This also assumes that governmental organizations are producing the same services as in the past but with less "overhead" or cost, although relatively few studies can support this claim. In fact, little evidence exists to support the notion that downsizing and reorganization within the defense department has produced more efficient organizations.

The Defense Contract Management Command (DCMC), part of the Defense Logistics Agency, is charged with managing a staggering number of defense contracts. Along with nearly all defense related organizations, DCMC has seen its personnel rolls drop steadily since 1990. This reorganization should have resulted in a lean, efficient command. The efficiency of the 65 Contract Administration Offices based in the United States that make up DCMC is the subject of this thesis.

In its most basic form, efficiency is a ratio of products (or outputs) to inputs. Regardless of the type of output and input, resulting efficiency is simply computed as outputs per input unit. For example: "Automobiles per dollar" is an effective means to compare efficiency between automobile factories producing similar products. Difficulties arise quickly when attempting to compare efficiency between units without

easily identifiable or countable inputs and outputs. Products from "white collar" workers such as managers and clerical staff are far more difficult to quantify. In private enterprise, profit is always available for use as the measured output. Because of the lack of a profit statement in the public sector, these organizations are often characterized by multiple outputs and occasionally multiple inputs (Ganley, 1992, p.2). The very nature of public sector efficiency analysis lends itself directly to the methodology known as Data Envelopment Analysis or DEA, which combines multiple output and input measures to produce a single efficiency score for each organization. DEA is the basis for the efficiency analysis of the 65 DCMC Contract Administration Offices.

B. BACKGROUND

Defense Contract Management Command (DCMC) provides contract management services for diverse products and services for most contracts awarded within the Department of Defense. DCMC manages over 350,000 contracts with 23,000 contractors worldwide totaling over $900 billion in unliquidated contractual obligations and employs over 14,000 employees (Defense Contract Management Command, 1998). In order to manage the implementation of these contracts after their award, DCMC, headquartered in Fort Belvoir, Virginia, is organized into three major districts: Eastern District, Western District, and International District. Each District is responsible for the control and supervision of several Contract Administration Offices (CAO) which provide continuous contract management services for government program managers overseeing individual manufacturers under contract to the Department of Defense (Defense Contract

Management Command, 1998). In this analysis, only Eastern and Western Districts are analyzed.

A total of 65 CAOs actively administer contracts for the districts in DCMC. Contract Administration Offices provide support for fact-finding and negotiations between contractors and contracting officers, provide safety and environmental assurance, evaluate contractor processes and controls, evaluate contractor corrective actions, provide control of government property, and provide an independent evaluation of contractor progress (Defense Logistics Agency, 1998).

In general, both the number of active offices in DCMC and the overall staffing level at each Contract Administration Office have reduced since 1990 due to Defense Department downsizing. Because of this, proper resourcing of Contract administration Offices has come into question. It is not known if individual CAOs are over or understaffed with respect to their assigned workload (Boyce, 1998).

Two types of CAOs operate within DCMC. Defense Contract Management Area Offices (DCMAO) manage contracts within a geographic area. Defense Plant Representative Offices (DPRO) are resident within contractors' plants and are responsible for administration services with that particular contractor only. Contract management includes daily, on-site surveillance of contractor systems and program specific concerns that cannot be viewed or monitored by off-sight agencies. The CAO organization allows DCMC personnel to reside close to or in contractors' facilities and to tailor their services to specific customers (DLA, 1998).

Of the 65 CAOs, nearly half are DPROs and half DCMAOs (34 and 31 respectively). The greatest difference between area offices and plant offices is the size

and number of contracts managed. Area offices tend to manage many (sometimes thousands) of contracts of limited size and scope. Plant offices manage fewer contracts with a specific contractor but each contract generally has a larger value and associated complexity. For this reason, measures of production output for these two types of offices are quite different. Area offices tend to measure output by quantity of contracts managed while plant offices tend to use the size or dollar value of the contract managed.

Because of the inherent differences in the two CAO types, (different management techniques, volume, type, and complexity of work), DCMC management has determined that each office type should be modeled separately. The two models are referred throughout this text as the Plant Office Model for DPROs and Area Office Model for DCMAOs.

As will be shown in following chapters, the methodology known as Data Envelopment Analysis (DEA), a mathematical programming technique, provides a methodology to determine efficiency among public sector organizations with multiple input and output measures (Norman, 1991, pp. 5-8). When implementing DEA models, a great deal of care must be taken when selecting measures for inclusion in the model. Data analysis techniques of the potential input and output measures guide the modeler to select not only the proper measures for the model, but also the appropriate DEA model formulation.

Once the measures and specific DEA model are selected, an efficiency score is computed for each office. These scores not only identify inefficient and efficient offices, they also suggest potential improvement strategies for inefficient offices.

In Chapter II, a brief discussion of Data Envelopment Analysis and its relevance for this study is investigated. Chapter III determines which potential input and output measures the proper attributes for inclusion in a DEA model. Chapter IV shows the final formulation of the DEA model and discusses the results as well as insights into the sensitivity of the model and potential improvements for inefficient offices. Recommendations and conclusions are provided in Chapter V.

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II. METHODOLOGY: DATA ENVELOPMENT ANALYSIS

A. EVALUATING CONTRACT ADMINISTRATION OFFICES

The combined effect of Defense Department downsizing and subsequent reduction in defense related acquisition of goods and services has been reduction in both the number and size of contracts managed by DCMC. Some CAOs have consolidated or closed, sometimes increasing the workload at a CAO, but in general, workload has decreased (Boyce, 1995, p. 11).

Proper staffing of individual CAOs at DCMC has long been a subject of debate. No effective means of scientifically determining the proper staffing level existed until very recently. In 1995, the Defense Logistics Agency Office of Operations Research and Resource Analysis fit a linear regression model of staffing as a function of workload (Boyce, 1995). Proper resourcing was then taken to be the value of the predicted staffing from the regression line for a particular workload. Two separate regression models, one for plant offices and one for area offices were used to determine staffing. A feature of these regression models is that a few offices with great influence may induce an improper target staffing level (either too high or too low). Using regression also assumes the notion that an "average" office exists without taking into account the unique missions of different offices. Most importantly, the regression methodology does not clearly identify offices that are particularly efficient and establish targets for the remaining offices to reach. In fact, the regression model could lead decision makers to add personnel resources to an efficient office because its outputs per unit input do not conform to the

average. A better response is to identify the efficient CAOs as the benchmark for other offices to emulate.

Determining relative efficiency between these offices a better method for comparing their performance. If every CAO produced exactly the same products, simple ratios of inputs and outputs could be used to compute relative efficiencies easily. The offices can be ranked by their efficiency of outputs / unit input. This metric gives great insight into those offices with the best business practices. If one "best practice" office can gain two outputs per unit input, surely all offices should strive to attain that goal.

However, a fundamental problem arises when more than one input or output is necessary for relative efficiency comparisons. It is possible that an office may produce a lot of one output but relatively little of another. A composite efficiency score can be computed by taking the mean efficiency score. Alternatively, management could assign a weight or relative importance to each output or input, thereby developing a weighted average efficiency for each office. Unfortunately, both of these methods impose certain assumptions on the underlying data. In the first case, each output and input is assumed to be equally vital to each office's overall efficiency. In the case of management determined weights, the assumption is that those heuristically developed weights are valid and that they apply to every office. The "one size fits all" approach is not always appropriate. In particular, for organizations that may have different contexts or environments in which to work, there may be great variability among output and input measures.

What truly is required, in order to find a fair measure of an office's efficiency, is an efficiency score that is *optimal* for that office: an efficiency score which has the best

weight on each output and input so that an individual office achieves the highest possible score. This provides each office with an evaluation of its inherit efficiency based on its strengths. This is exactly how Data Envelopment Analysis computes relative efficiency scores with multiple inputs and outputs and why it offers an excellent methodology to determine the efficiency of Contract Administration Offices.

B. DATA ENVELOPMENT ANALYSIS

1. Overview of the Methodology

Data Envelopment Analysis (DEA) is a mathematical modeling methodology that determines a Decision-Making Unit's (DMU) efficiency using non-linear programming techniques. (Because each non-linear program is a fractional program, it can be easily translated into an equivalent linear program.) Decision Making Units are production nodes that transform the inputs into outputs. For the purpose of this research, CAOs are the DMUs.

Originally developed by Charnes, Cooper, and Rhodes in 1978 (Charnes, 1994, pp. 23-25), DEA models calculate an efficient frontier by comparing each DMU's inputs and outputs. The efficient frontier is composed of DMUs that have attained the maximal efficiency score of one. All other offices, those that are inefficient, have an efficiency score less than one and are not on the frontier. The DEA model determines a relative efficiency score for each DMU which represents how far the DMU is from an efficient frontier (Norman, 1991, p. 43).

In order to calculate the efficiency of a particular DMU, mathematical programming techniques are used to determine "virtual multipliers" or "weights" for the

relative value of the various outputs and inputs that maximize a specific DMU's efficiency score. The weights are thus the primal variables in the mathematical program. A particular DMU may utilize any combination of inputs and outputs in order to maximize its own efficiency score subject to the constraint that all other DMUs' efficiency scores using that particular DMU's weights are less than or equal to one. A separate linear programming formulation is used to calculate the efficiency score for each DMU. It is important to note that DEA models produce only relative efficiency scores in comparison to all other DMUs. Unlike regression techniques that estimate an average production function, DEA techniques identify two subsets of DMUs: the efficient and inefficient.

2. Model Formulations

The two most prevalent DEA model formulations are the model developed by Charnes, Cooper, and Rhodes (1978), and the model developed by Banker, Charnes, and Cooper (1984), called the CCR and BCC models respectively. The most simple, the CCR, is formulated in Figure 1.

Indices:

i	Output Types (1,2,...I)
j	Input Types (1,2,...J)
k	DMUs (1,2,...K)

Data:

x_{kj}	Value of input j for DMU k
y_{ki}	Value of output i for DMU k
ε	A small constant.

Variables:

v_j	Weight on input j (unitless)
w_i	Weight on output i (unitless)

Formulation:

For each DMU o, (o = 1,2,...K)

$$\text{Maximize} \quad \frac{\sum_i y_{oi} w_i}{\sum_j x_{oj} v_j}$$

Subject to constraint:

$$\frac{\sum_i y_{ki} w_i}{\sum_j x_{kj} v_j} \leq 1, \quad \text{for } k = 1,2,\ldots K$$

$$w_i \geq \varepsilon, \quad \text{for } i = 1,2,\ldots I$$
$$v_j \geq \varepsilon, \quad \text{for } j = 1,2,\ldots J$$

Figure 1. CCR DEA Model Formulation (Norman, 1991, p. 235)

The most significant difference between the formulations of the CCR model and BCC model lie in how the model accounts for output / input returns to scale. The CCR model assumes *constant returns to scale*, such that an increase in an input parameter has a corresponding and constant increase (or benefit) in an output parameter. The BCC model accounts for *variable returns to scale.* This occurs when the benefit in output per unit input decreases as the input becomes larger. The basic BCC formulation, given in Figure 2, is quite similar to the CCR model except for the addition of a constant, ***c***, in the objective function.

Indices:

i	Output Types (1,2,...I)
j	Input Types (1,2,...J)
k	DMUs (1,2,...K)

Data:

x_{kj}	Value of input j for DMU k
y_{ki}	Value of output i for DMU k
ε	A small constant.

Variables:

v_j	Weight on input j (unitless)
w_i	Weight on output i (unitless)

Constants:

c_k	Constant for each DMU k

Formulation:

For each DMU o, (o = 1,2,...K)

$$\text{Maximize} \quad \frac{\sum_i y_{oi} w_i + c_o}{\sum_j x_{oj} v_j}$$

Subject to constraint:

$$\frac{\sum_i y_{ki} w_i + c_o}{\sum_j x_{kj} v_j} \leq 1, \quad \text{for } k = 1,2,\ldots K$$

$$w_i \geq \varepsilon, \quad \text{for } i = 1,2,\ldots I$$
$$v_j \geq \varepsilon, \quad \text{for } j = 1,2,\ldots J$$

Figure 2. BCC DEA Model Formulation (Norman, 1991, p. 247)

C. CONCLUSION

Data Envelopment Analysis provides an appropriate approach for determining the efficiency of Contract Administration Offices. The first and most challenging step in formulating a DEA model is the selection of the input and output measures. The following chapter will determine the best collection of measures from a field of available

statistics to use in the two CAO models. The measures for each model will be selected separately, so that only the most appropriate data is selected for those models. Finally, the relationship between output and input measures is investigated in order to select the proper DEA formulation: CCR (constant returns to scale) or BCC (variable returns to scale). Once the model is formulated, insights into the efficiency of DCMC are made and improvement strategies observed. These efficiency scores can be used by management to assist in determining the proper resource requirements for these offices.

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III. MODEL FORMULATION

Selection of inputs and outputs for Data Envelopment Analysis models is at the center of the model formulation. The challenge resides in determining the proper measures that most accurately, completely, yet succinctly describe the true effectiveness of Contract Administration Offices in the two models to be formulated (Plant Model and Area Model). In this chapter, after briefly describing the data, its origin, and some if its characteristics and limitations, the relationship of the inputs to the outputs will be analyzed in order to determine their possible contribution in the two DEA models.

Public sector organizations often are forced to rely on subjective, rather than objective measures of performance because what may be assumed to be outputs, are often assigned requirements, not under the control of the organization. That is, increases or reductions in inputs may not affect outputs at all. The effect of reducing an input, while increasing efficiency score, may only reduce the quality of service of that particular office. In the case of DCMC, a combination of subjective and quantitative measures are available for analysis and possible inclusion in the DEA model.

Charnes, in his seminal work with DEA, stated that in general, not more than one measure should be included for every three evaluated Decision Making Units (DMU) (Charnes, 1994, p. 73). (As the number of measures approaches the number of DMUs, the proportion of DMUs evaluated as efficient will approach 100%. Each added measure, in effect, provides another factor in which the DMU attempts to maximize its efficiency score). As the DCMC models contain 31 DMUs for the Area Model 34 DMUs for the Plant Model, every effort to maintain fewer than 10 measures of inputs and outputs in total must be taken.

Finally, a positive relationship should exist between selected inputs and outputs. As the inputs in the data set generally increase, the expected result is an increase in the associated outputs.

A. DATA DESCRIPTION AND INITIAL MEASURE SELECTION

A panel of subject matter experts at DCMC chose candidate input and output measures for further analysis based on their knowledge of the core performance requirements of these offices. They determined that all CAOs perform certain core tasks that account for the vast majority of the workload and additionally are evaluated on key quality measures. Thus, the candidate output factors measure aspects of workload and performance quality (Russell, 1998).

1. Databases

Three databases maintained by DLA provide the candidate input and outputs: The Performance Labor Accounting System (PLAS), Mechanization of Contract Administration Services (MOCAS) database, and the Automated Metric System (AMS) database. All data analyzed was collected in fiscal year 1998 and usually includes totals for the year. In certain cases (as noted) averages or other measures are used. In general, non reported data is given a default value of zero.

The Performance Labor Accounting System (PLAS) records every hour worked by an individual staff member for a particular CAO and records the type of work he or she is accomplishing for that hour. Employees, regardless of position, are required to record hours worked according to the kind of contract (contract kinds are defined as

Systems Acquisition, Research and Development, Maintenance and Facilities, Service, Supply, and Subcontracts), and by the type of work (inspections, audits, cost analysis, etc.). The PLAS data base enables rapid computation of the number of hours worked at a particular office in a given time period (DCMC Unit Cost, 1998, p. 6).

The MOCAS database tracks contracts by kind and their value. This data base provides a count of the contracts managed by each CAO as well as their outstanding dollar value (unliquidated obligations). These two measures serve as candidates for workload (number of contracts and value of contracts) and may be used as outputs in the model, (Defense Logistics Agency, 1998).

The Automated Metric System (AMS) provides key measures of performance to DCMC management on each CAO. Certain key measures that Defense Contract Management Command uses for management decisions are the following: Overhead costs per hour of mission related work, customer satisfaction rate, contractor on-time rate, and the value of savings to the government resulting for actions taken by a particular CAO. (DLA, 1998). Each of these measures are candidate outputs for the efficiency model.

2. Candidate Inputs and Outputs

The DCMC provided ten separate data elements for each CAO. These measures will each be explained in this section and are summarized as follows: Hours Worked, Performance Based Activity Measure, Customer Satisfaction factor, On-Time rating, Supply Contracts Managed Per Month, Other Contracts Managed Per Months, System

Acquisition Contracts Value Managed Per Months, and Return on Investment, and Overhead Costs per hour.

a. Inputs

The total number of hours worked in a year can be further divided into component parts by contract kind. Because DEA methodology considers each input and output equally, the DEA model may base an efficiency score on a single input measure, such as total hours for one contract kind. For this reason, the subject matter experts specified that the input measure be total hours worked in a given year. The most complete and current data is for fiscal year 1998 (DCMC Unit Cost, 1998, pp. 4, 10-12).

b. Outputs

Considerable effort has been spent at DCMC in an attempt to properly quantify the products of CAO efforts. A difficulty in quantifying products is the fact that CAOs do widely varying work based on differing contract kinds and contractors overseen. The most common output measure employed by DCMC is simply a count of the number of contracts managed in a given month (contracts managed per month or CMM). This measure, provided by the MOCAS data base, is derived from the number of contracts that have seen activity at the close of a particular month. Using CMM as a production unit has obvious drawbacks because it does not take into account the size, risk or complexity of a particular contract. For example, contracts for major new systems (tanks, trucks, ships, etc.) normally have a great deal of complexity, risk, and associated

work where recurrent supply or facilities contracts do not (DCMC Unit Cost, 1998, pp. 10-11).

As a means to partition the data set, contracts are categorized as one of three kinds. System acquisition, Supply, and Other contracts. Systems acquisition contracts, the most complex and high dollar valued contracts, are not normally measured in terms of CMM. Because of their relatively low quantity and high value, they are considered as a separate category. Supply contracts are the greatest single subset by contract kind in the CMM data set, making up 28% of the total count of contracts within DCMC. To provide further insight into components of the eventual efficiency score, supply contracts were also separated from the total and used as a candidate output.

The remaining contract kind, systems acquisition is measured by its size or value remaining to be filled for the government. This unfilled obligation is called "unliquidiated obligations" in DCMC literature and is measured in units of millions of dollars.

The Return on Investment (ROI) is the sum of all savings to the government as a result of actions taken by a particular CAO. Examples of some of these actions are price negotiations, production process improvements, refunds, costs recaptured through litigation, and compensation for the unauthorized use of government property. This output is a direct result of cost saving measures taken by CAOs and is measured in millions of dollars in savings (DCMC Unit Cost, 1998, p. 24).

The Customer Satisfaction rating, provided by the AMS database, is a subjective measure of performance graded by purchasing authorities, such as government program managers, whenever they request and utilize CAO services. Each office

received a score between one and six, where six was a perfect score (DCMC Metric Guide, 1998, p. 81). Unlike most other data elements, this measure is an average score that was tallied when more than one rating was received in FY98. Unfortunately, the reporting rate is estimated to be only 20% (Kuhl, 1998) and fully 12% of all offices have no rating. Further, little relation between the candidate input (total hours worked) and customer satisfaction exist (as will be shown). However, this is the only measure of CAO service quality available; certainly an important aspect of efficiency. Despite its shortcomings, management at DCMC feel that the customer satisfaction rating is a significant factor to include in overall performance evaluations.

The On-time rate factor for a CAO is a measure describing each managed contractor's ability to meet production time lines set forth in their contract with the government. CAOs influence the on-time rate indirectly by providing timely and appropriate services to facilitate the rapid fulfillment of the contract. This is also an average rate based on contract deliveries for FY98 (DCMC, Metrics Guide, 1998, p.83).

3. Environmental factors

DCMC selected two other data elements as candidates for variables in the model. However, neither of these are truly an input or an output even though they may have a descriptive nature regarding the efficiency of CAOs. As environmental factors, these measures are useful in providing explanations about the behavior of the model and in one case, may be included in the model, although not as a unique measure.

The factor called the Performance Based Activity Measure (PBAM) is a measure of the relative risk an individual office must work under (DCMC, 1996, p. 45). To

measure this risk, factors such as experience level of contractors, complexity of contracts, and administrative overhead for particular offices based on their assigned contracts were scored to show that higher risk requires more inputs. Offices were assigned a rating between 3 and 9 with higher factor equating to higher relative risk. The implication is that offices with higher risk factors require more input for proper and adequate management. In terms of the efficiency model, an office with a higher PBAM rating can be expected to require more input resources to gain the same quantifiable outputs as offices with lower PBAM rating.

To accommodate this factor in the model, each output can be scaled by the PBAM factor (or each input by the inverse of PBAM). The effect of the scaling is to normalize the data with respect to risk. Those offices that "expect" to have more inputs for the same quantifiable output, have thus been equalized with their counterparts that have a lower associated risk. Once the DEA model is completed and evaluated, the PBAM scaling factor can be multiplicatively removed to determine true improvement strategies.

The second environmental factor is a measure of indirect costs per hour for each CAO. This can be analyzed as an overhead cost per hour of doing business. Examples of overhead costs are hours billed as a result of training or clerical work not related directly to contract administration. This factor, too, does not resolve itself as an input or an output but is rather a descriptive measure of management practice. Once efficiency scores are determined it may serve as a comparative tool to determine if a correlation exists between efficient offices and their associated overhead costs or if a "best practice" or target overhead cost exists.

For simplicity, each of the two candidate inputs, six candidate outputs, and two environmental factors are labeled in a brief format from the following table. Each is referred to throughout this text by their abbreviated names.

Type	Description	Units	Abbreviation
Input	Total hours recorded by CAO in fiscal year 1998	hours	Hours
Input	Total hours recorded scaled by inverse of PBAM factor	hours	S.hours
Output	Customer satisfaction rating	unitless	CustSat
Output	On - time delivery factor	% on time	Ontime
Output	Millions of dollars of unliquidated contract value managed per month, for systems acquisition contracts only. (Total for fiscal year 1998)	dollars (million)	MUMM
Output	Supply contracts managed per month (Total for fiscal year 1998)	contracts	SupCMM
Output	Contracts managed per month for all other contract kinds. (Total for fiscal year 1998)	contracts	OthCMM
Output	Return on investment (Total fiscal year 1998)	dollars (million)	ROI
Environmental	Performance Based Activity Measure	unitless	PBAM
Environmental	Overhead costs per billed labor hour	dollars	Overhead

Table 1. Candidate Measures

B. ANALYSIS OF CANDIDATE MEASURES

In order to show a ratio of inputs to outputs as meaningful in a relative efficiency model, increases in inputs must be shown to increase outputs (Norman, 1991, p. 69). Further, if the CCR model is to be used, these relationships must be linear. In each analysis, data was partitioned into two sets: One for geographical area offices, and one for plant representative offices.

1. Analysis Of Linearity

Figures 3 and 4 show all pairs of plots for the eight measures of Table 1 for Area Model and Plant Model respectively. In this case, clear relationships are difficult to ascertain in certain instances. However, even those measures with the most scattered data points, such as OnTime, do show an increasing pattern with respect to inputs. No evidence of non-linearity exists in any of the measures from either of the models. Due to some instances of non - reports in the CustSat data and ROI data, these plots tend to look bi-modal. Specifically, the customer satisfaction rating tends to be between 5 and 6, or a default value of zero if no report is given. When non-reporting activities are removed from both CustSat and ROI, a more linear trend appears in the data plots for each model.

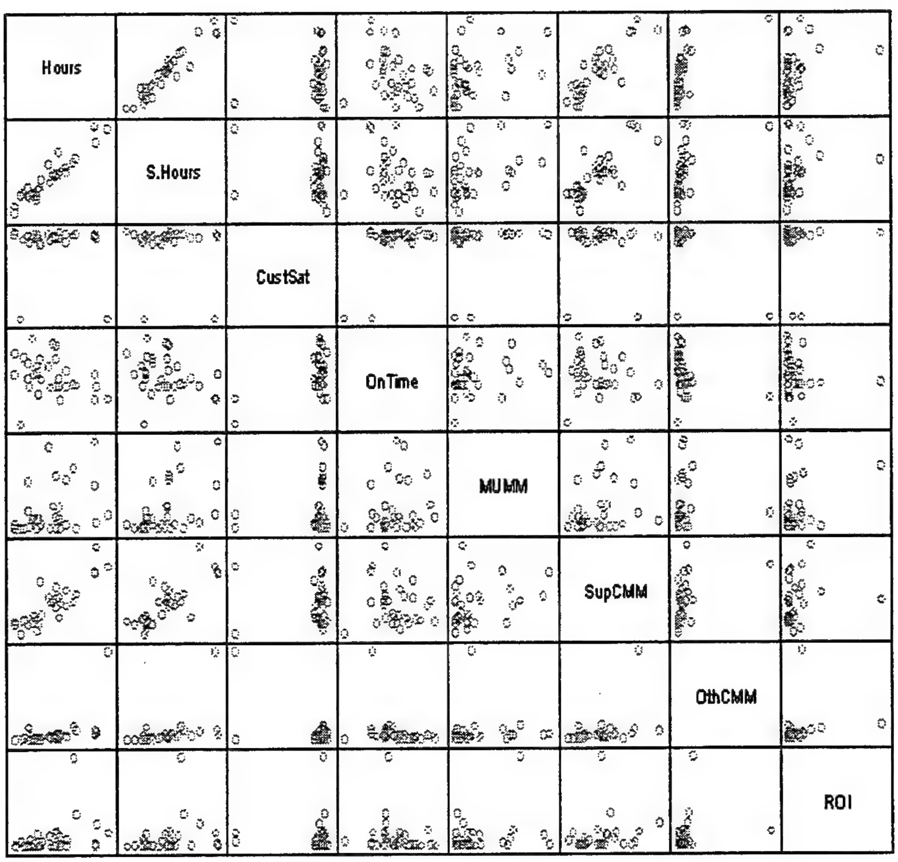

Figure 3. Area Model Scatter Plots, Pairs of Candidate Measures

A significant conclusion is therefore drawn that each output can be modeled as linear with respect to input and no transformations of data are necessary. Neither do decreasing returns to scale need to be accounted for in the DEA model.

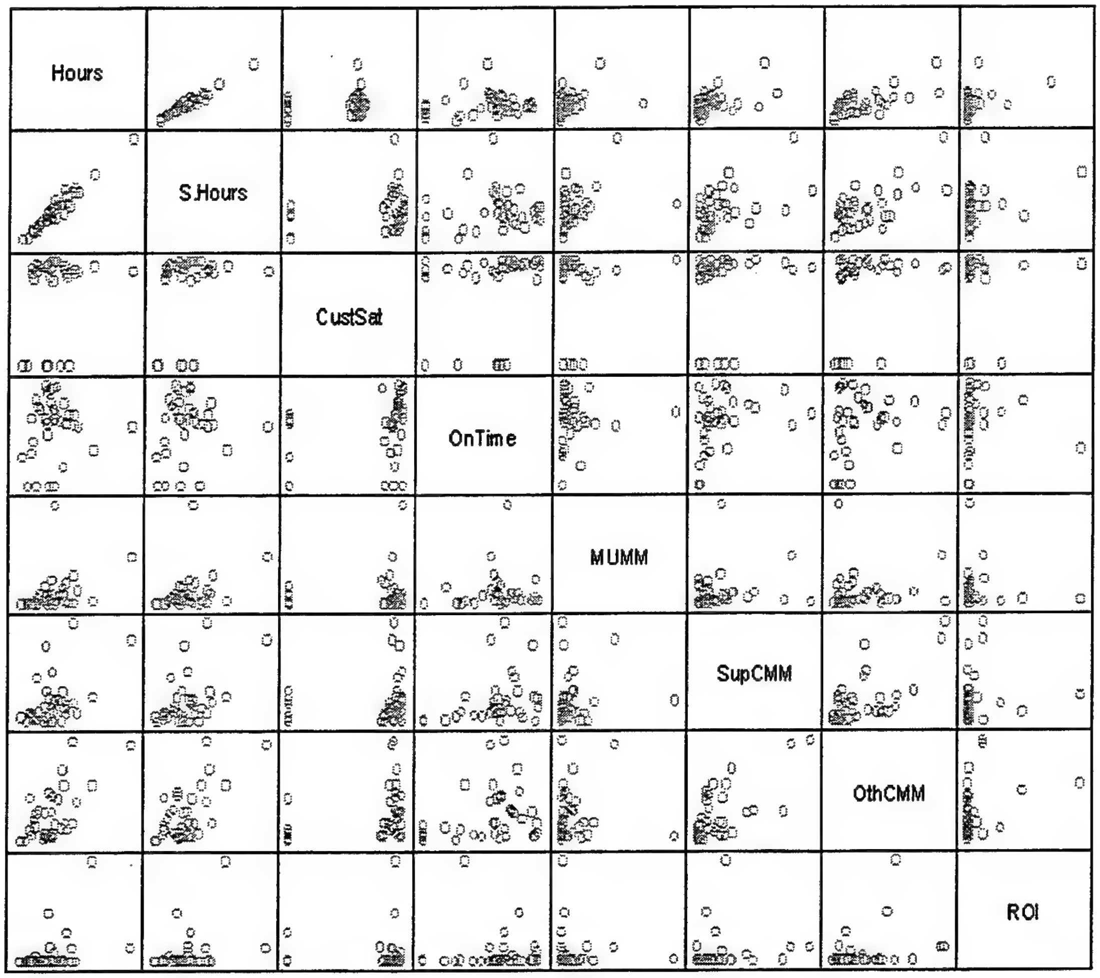

Figure 4. Plant Model Scatter Plots, Pairs of Candidate Measures

2. Correlation Analysis

Because of the linear nature of the data, analysis of the pairwise correlation coefficients between inputs and outputs gives a relative strength of this linear relationship. Tables 2 and 3 show the correlation between each measure for both model sets. Positive correlation between inputs and outputs indicates a strong candidate for

inclusion in a DEA model. However, strong correlation between inputs with other inputs and outputs with other outputs may indicate a redundancy in the measurement of one or more of these factors. Each factor, among its peers of inputs or outputs should measure a unique factor to the greatest extent possible.

As suspected, the two input measures are highly correlated in both models, indicating that only one, not both, input measures should be chosen. Further, an arbitrary selection of one of these two inputs for inclusion in a model would not have a great impact on the overall result of the model. The real goal of scaling the input hours is not to affect the average outcome but to impact efficiency scores of offices individually.

	Hours	**S.hours**	CustSat	Ontime	MUMM	SupCMM	OthCMM	ROI
Hours	**1**	**.95**	**-.13**	**-.30**	**.37**	**.87**	**.54**	**.34**
S.hours	**.95**	**1**	**-.16**	**-.30**	**.48**	**.81**	**.50**	**.26**
CustSat	**-.13**	**-.16**	1	.50	.17	-.06	-.62	.01
Ontime	**-.30**	**-.30**	.5	1	.17	-.17	-.30	-.15
MUMM	**.37**	**.48**	.17	.17	1	.29	.03	.29
SupCMM	**.87**	**.81**	-.06	-.17	.29	1	.43	.21
OthCMM	**.54**	**.50**	-.62	-.30	.03	.43	1	.21
ROI	**.34**	**.26**	.01	-.15	.29	.21	.21	1

Table 2. Correlation Coefficients for Measures, Area Model

	Hours	**S.hours**	CustSat	Ontime	MUMM	SupCMM	OthCMM	ROI
Hours	**1**	**.97**	**.19**	**.11**	**.36**	**.49**	**.64**	**.40**
S.hours	**.97**	**1**	**.22**	**.12**	**.40**	**.52**	**.65**	**.36**
CustSat	**.19**	**.22**	1	.20	.11	.16	.28	.05
Ontime	**.11**	**.12**	.20	1	.16	.35	.22	.01
MUMM	**.36**	**.40**	.11	.16	1	.13	.01	-.07
SupCMM	**.49**	**.52**	.16	.35	.13	1	.66	.10
OthCMM	**.64**	**.65**	.28	.22	.01	.66	1	.31
ROI	**.40**	**.36**	.05	.01	-.07	.10	.31	1

Table 3. Correlation Coefficients for Measures, Plant Model

The contract count measures (SupCMM and OthCMM) are also relatively highly positively correlated with each other. This indicates that offices that manage a large

number of supply contracts also manage a large number of other contracts. Although it is possible that an aggregate count of total contracts managed may provide a more meaningful result in the final efficiency analysis, aggregation also serves to dilute the effect of the major component of the CMM factors (supply contracts count) as a separate measure of output. For this reason, two CMM factors will remain. The similarities in the two data sets are substantial, however, key differences can be highlighted.

a. Defense Contract Management Area Offices

In the Area model, a high positive correlation exists between each input candidate and the two contract count measures. A somewhat lower correlation with MUMM as well as the ROI factor also exist. These four measures seem to be the core output measures in this model with respect to Hours and S.hours. A negative relationship exists for the Customer satisfaction and On-time rate. The Ontime correlation of -.3 admits that most likely no positive relation does exist with the input. It is probable that an increase in hours has no effect on any contractor's ability to meet his contracted schedule.

In fact, the results of a two tailed test of the null hypothesis of zero correlation on each of the correlation coefficients, (at a .05 level of significance), show that most likely no correlation exists between ROI, CustSat, or OnTime with either Hours or S.Hours. (The other measures show strong evidence of correlation.) These three uncorrelated measures constitute half of the potential outputs in the model. However, this result is not completely unexpected as the current staffing levels have been assigned with the regression model (discussed in Chapter II) utilizing only workload as

the modeled variable. The three uncorrelated measures have never been "rewarded" with additional staff resources in the past. It is possible that after implementation of a model for staff resourcing that does reward these measures, correlation will increase. In any case, the inclusion of customer satisfaction rating and on-time factor will simply serve as another factor for the offices with a high scores in these metrics to take advantage of in the DEA methodology. Additionally, they are the only qualitative measures available, and as such, must be included in the model formulation. Chapter IV will consider some measures to limit their overall effect on the efficiency scores calculated.

b. Plant Representative Offices

Relationships in the Plant Representative model are much more clear. Every input and output relationship is indeed positive although those relationships vary greatly in their magnitude. The greatest correlation exists in what appear to be the core measures with respect to hours and scaled hours: MUMM, SupCMM, OthCMM, and ROI. But a different correlation than in the area model exists with customer satisfaction rate. This may be in part due to the lower reporting rate among plant offices for this factor (82% in plants versus 94% for area offices) and higher average score.

The on-time rate factor, while positively correlated with scaled hours at .12 or with hours at .11 is still the lowest, by far, of all other measures. The results of a two tailed test of zero correlation on each of the correlation coefficients, (at a .05 level of significance), show that likely no correlation exists between the CustSat or OnTime measures with either Hours or S.Hours. Unlike the Area model, ROI does show evidence

of correlation. As in the Area Model, these factors may be included in the model, with restrictions on its overall effect.

c. The Effect Of Management

As noted earlier, CAOs have been resourced according to a regression model utilizing workload against staffing. It is likely that this method of resourcing has served to undermine the correlation of output measures not related to that regression model (on-time rate and customer satisfaction). Further, even though measures of quality were not required in the regression model, they are absolutely necessary in an efficiency model where outputs are assigned rather than under the control of office management. For these reasons, quality measures, regardless of their negligible statistical correlation with the input must be included in both models.

C. DEA MODEL FORMULATION

The linearity of every output / input plot implies that a constant return to scale relationship exists among them. Evidence suggests that a CCR DEA model formulation best fits the DCMC data for efficiency evaluation. The general CCR model general formulation shown in Chapter II can be reformulated as a linear program with the specific parameters and indices from the DCMC data as follows:

Indices:

i Output Types (SupCMM, OthCMM, MUMM, ROI, CustSat, OnTime)

j Input Types (Hours or S.Hours)

k DMUs (Contract Administration Offices (1 to 34 for Plant Model and 1 to 31 for Area Model))

Data:

x_{kj} Value of input j for DMU k

y_{ki} Value of output i for DMU k

ε A small constant.

Variables:

v_j Weight on input j (unitless)

w_i Weight on output i (unitless)

Formulation:

For each DMU o , o = 1,2,...K

Maximize $z_o = \sum_i y_{oi} \; w_i$

Subject to:

$$\sum_j (x_{kj} \; v_j) - \sum_i (y_{ki} \; w_i) \leq 0, \quad k = 1,2,\ldots K$$

$$\sum_j x_{oj} \; v_j = 1$$

$$v_j \geq \varepsilon, \quad j = 1,2,\ldots J$$

$$w_i \geq \varepsilon, \quad i = 1,2,\ldots I$$

Figure 5. Linearized CCR Formulation (Norman, 1991, p. 236)

A total of 65 linear program solutions are required for the two models for DCMC, one for each DMU.

D. CONCLUSIONS

The DEA models for both Plant and Area offices will be CCR DEA models that contain either total hours or scaled hours as the input. Comparisons between the two input factors will be considered after model formulation. Outputs in each model will be

CustSat, SupCMM, OthCMM, MUMM, ROI and OnTime. Even though correlation analysis of the "quality" type measures do not suggest inclusion in the model, they are absolutely necessary for implementation in this model because all other outputs are assigned rather than under the control of the individual office management team. The qualitative measures are required to ensure that the assigned outputs are being performed well (Ganley, 1992, p.36).

The following chapter will outline the final model formulation for each office type and discuss the results of the CCR DEA models for both plant and area models. Also suggested improvement strategies for individual inefficient offices will be analyzed.

IV. MODEL RESULTS AND ANALYSIS

The two DEA efficiency models (Plant Office Model and Area Office Model) are created with one input parameter and six output parameters. Because of the general linear relationship between the input and output values, the DEA formulation that assumes constant returns to scale was used to express an optimally weighted ratio of outputs to inputs. The CCR formulation, outlined in Chapters II and III produced optimal efficiency scores for each evaluated Contract Administration Office.

Here, Decision Making Units (DMU) are Contract Administration Offices, the set of inputs is either Hours or S.Hours, and the set of outputs are SupCMM, OthCMM, MUMM, ROI, CustSat, and OnTime. The 65 fractional programs, (34 for Plant Model and 31 for Area Model), which can be equivalently expressed as linear programs (LP), were solved with the General Algebraic Modeling System (GAMS), utilizing the OSL solver.

In this chapter, a final formulation of the two models is presented after analyzing two unanswered questions from the previous chapter: What is the proper input measure? How can limits on the un-correlated metrics be imposed? Once the models are finally formulated, analysis of efficiency scores and insights into improvements for inefficient offices can be made.

A. FINAL MODEL FORMULATION

1. Effect Of Risk Factor Scaling

The effect of scaling hours by risk factor was unknown prior to modeling but expected to slightly lower efficiency in low risk offices and slightly raise efficiency in

those with high risk while not appreciably changing the average efficiency score over all offices. This should assure that offices with high risk are not penalized because their workload requires a greater input expenditure by its very nature and that low risk offices are not given an unfair advantage. By scaling the input hours, the intended result is that those offices with low risk will have to "work harder" to achieve efficiency than those with high risk.

The resulting efficiency scores show decisively that this is the case. A comparison of the aggregated mean efficiency score for each model for each different input, shows that a very small change took place (see Table 4). The change from un-scaled hours to scaled hours in the Area Model resulted in a slight decrease in average score from 76.36% to 75.47% while in the Plant Model a slight increase from 72.88% to 74.78% was shown. The conclusion is that the scaling factor has little impact on the average efficiency score.

In examining the score changes for each individual office between the two models, the greatest impact of scaling can be seen in the extreme cases. The five lowest risk and five highest risk offices show the most dramatic score change.

Five Offices with Lowest Risk	Score no Scaling	Score with Scaling	change	% change
Area Office 31	100.00	100.00	0.00	0.00%
Area Office 23	45.88	34.11	-11.77	-25.66%
Area Office 19	100.00	100.00	0.00	0.00%
Area Office 25	78.39	55.14	-23.25	-29.66%
Area Office 20	98.37	74.47	-23.90	-24.29%
Five Offices with Highest Risk	**Score no Scaling**	**Score with Scaling**	**change**	**% change**
Plant Office 17	49.48	67.20	17.72	35.81%
Plant Office 18	56.73	73.21	16.48	29.06%
Plant Office 23	55.06	61.23	6.17	11.20%
Plant Office 9	79.45	90.41	10.96	13.80%
Plant Office 21	100.00	100.00	0.00	0.00%

Table 4. Risk Factor Scaling

Note that offices in Table 4 with low risk that were rated efficient in the un-scaled model remained so in the scaled model. The strength of these offices in outputs is evident in their ability to overcome the scaling up of its input hours with risk factor and remain efficient in comparison to all other offices. In the case of the high risk office that was efficient in the un-scaled model, a further decrease (or scale down) of its input hours, has no further effect as it is already able to maximize its efficiency score. Also of interest is the fact that the 5 lowest risk offices are all area offices and the 5 highest risk offices are all plant offices. The graphs below (Figures 6 and 7) show in detail the individual score changes as impacted by risk factor scaling of the model.

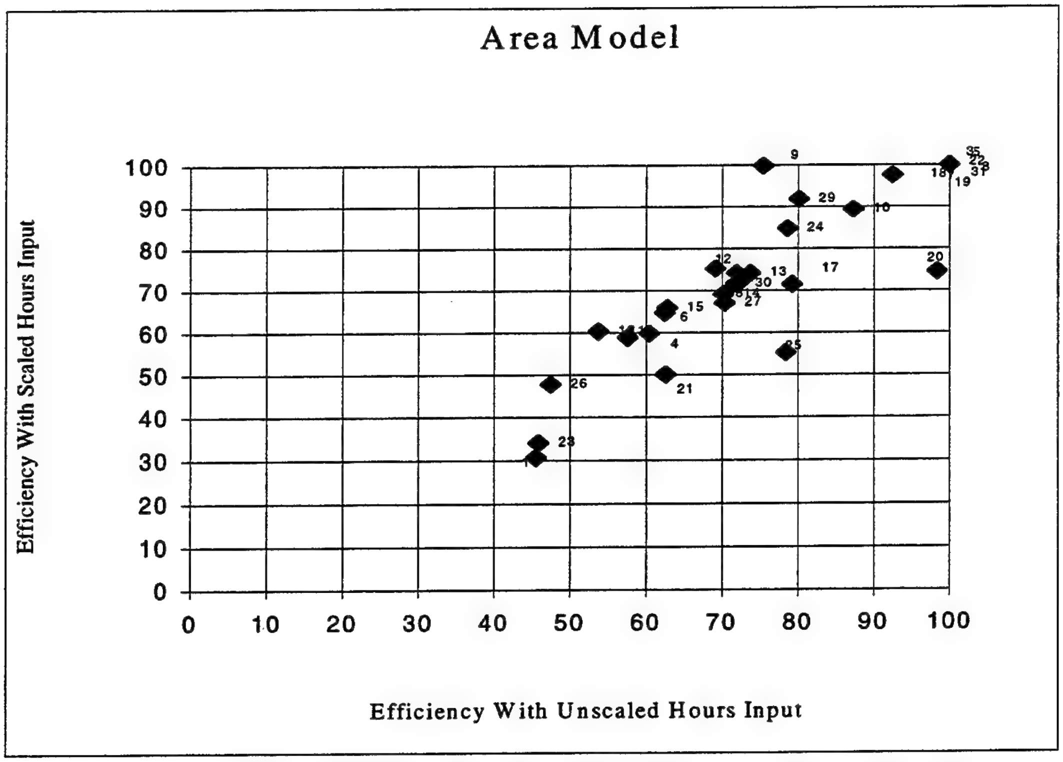

Figure 6. Area Model Efficiency Scores, Scaled Hours vs. Un-scaled hours

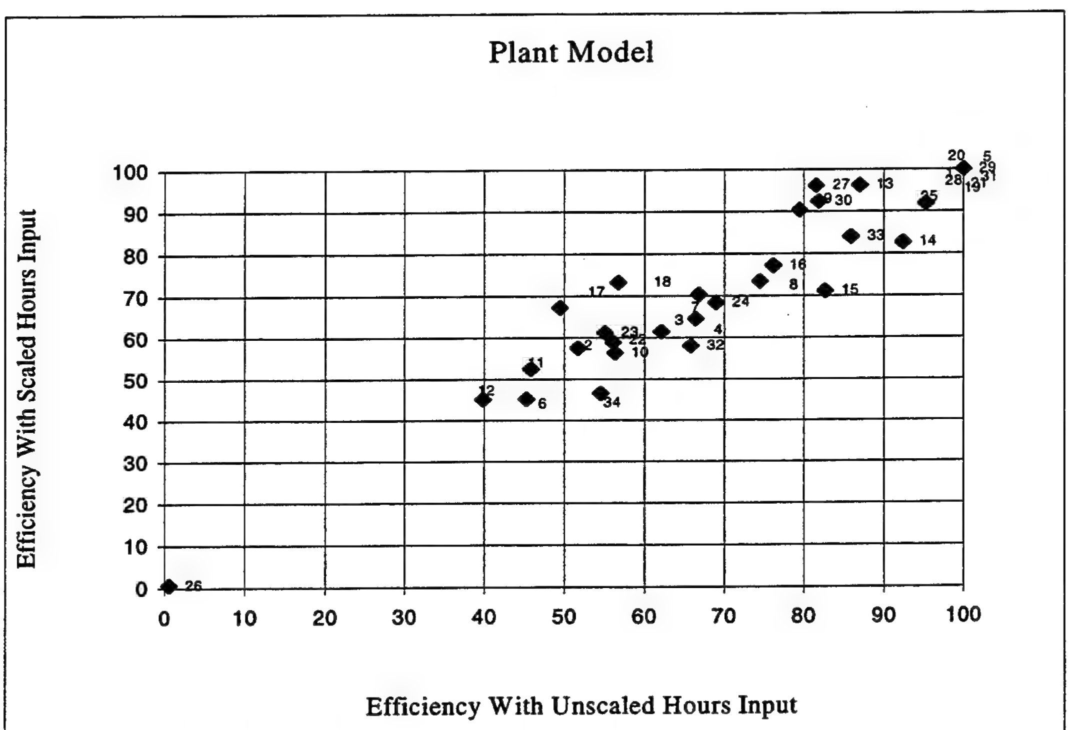

Figure 7. Plant Model Efficiency Scores, Scaled Hours vs. Un-Scaled Hours

The evidence supports the hypothesis that scaling by risk factor has the intended effect of equalizing the inputs for all offices based on inherent risk. For this reason, only models with the scaled input hours will gain further consideration for employment and refinement.

2. Effect Of Variable Constraints On Efficiency Scores

A great advantage of DEA methodology is the ability for each unit to be evaluated on its strengths. If the unit has only one strong parameter in a field of six, it is still possible to receive an efficiency score of one (100%). In this case, however, a few parameters did not display a positive relationship with the input parameter. An efficient rating for an office utilizing only one of those less strongly correlated factors should be limited in order to gain the greatest insight from the eventual scores. The problem is easily visualized when one assumes the worst case: An office with very few contracts to manage, with small dollar value, but with a very good OnTime and CustSat rating can certainly be evaluated as "efficient". In fact, the results of the models bear this out.

In the Area Model, without constraints on the maximum values of the weights, five of 31 offices rely on one of the weakly correlated parameters for more than 50% of their efficiency rating. In one case, fully 94% of the output weight (variable value of .94) is on the customer satisfaction rating. The effect on all offices are shown at Figure 8 with the most constraint sensitive offices labeled.

The Plant Model felt a significantly greater impact on efficiency scores with the imposition of variable constraints. Plant Model offices tend to rely on fewer parameters than do the Area Model Offices. This was expected because area offices manage

contracts from a wide variety of contractors and even wider range of contract kinds and types resulting in an efficiency score that combines many factors. In comparison, the plant offices, often with only one contractor to service, tend to be strong in only one or two performance measures. On average, Area Model offices used 3.5 output parameters in their efficiency score while Plant Model offices used only 2.6. As a result, the impact of constraints on two parameters is magnified in the Plant Model. Of concern, however, is the fact that three offices in the Plant Model relied completely on the customer satisfaction rating and fully 12 offices (35% of all plant offices) used the customer satisfaction rate for more than 75% of their overall efficiency score.

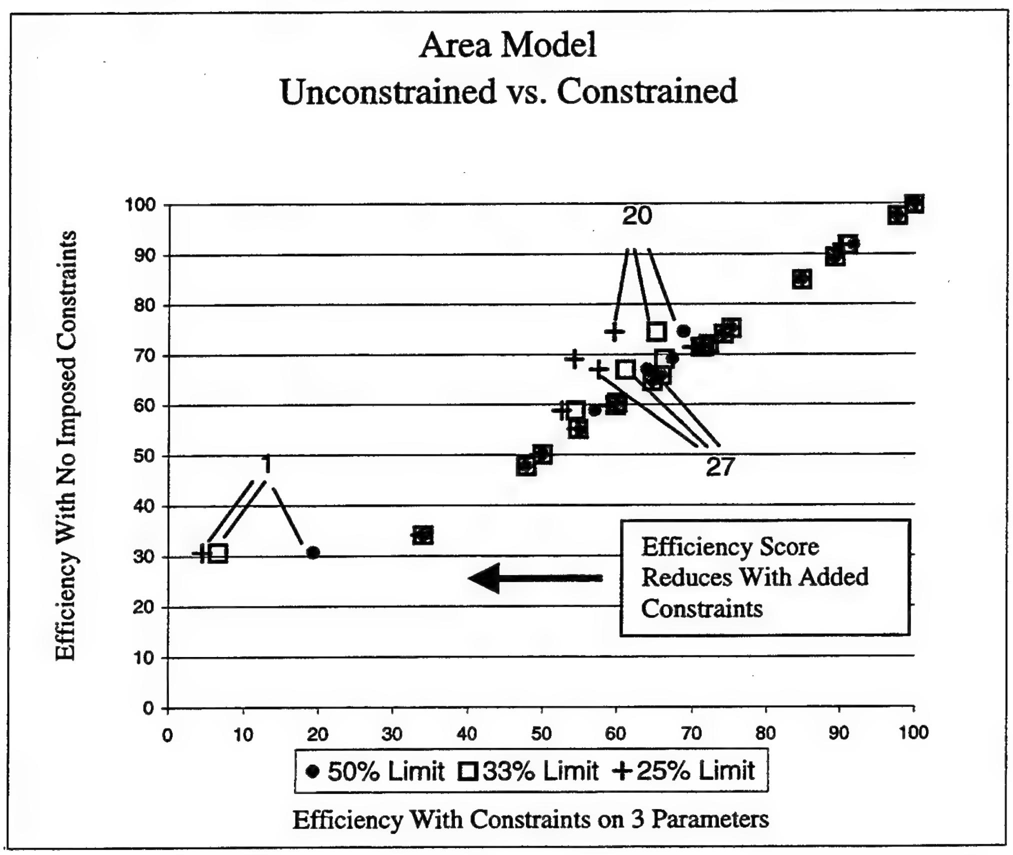

Figure 8. Area Model Constraint Impact on Efficiency Scores

Clearly, a limit on these factors is in order. An upper limit of 50%, 33%, or 25% on the statistically un-correlated parameters is imposed and has the effect of drawing down the score of the offices heavily dependant on them and forcing more reliance on the more highly correlated metrics.

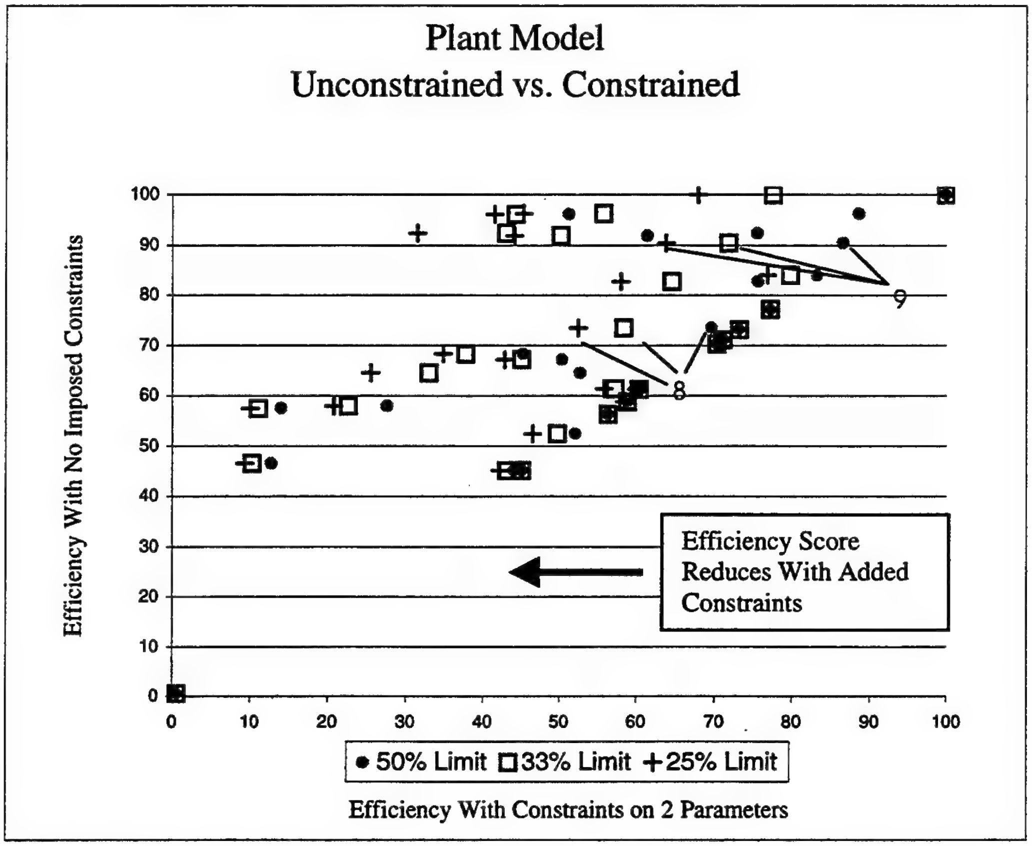

Figure 9. Plant Model Constraint Impact On Efficiency Scores

With the imposition of constraints, it is possible for offices to either receive the same score as in the unconstrained model or a lower score. In some cases this lower score is dramatic; the result of an over reliance on the un-correlated parameters for efficiency rating. The effect of the 25% and 33% constraint appear to be overly restrictive. The 50% constraint has the intended effect of significantly reducing the

efficiency score for offices that rely too heavily on those metrics. The more restrictive constraints begin to adversely impact offices that do not seem overly dependant on those parameters for their efficiency score. The 50% upper limit constraint on CustSat, OnTime, and ROI will be imposed in the Area Model, the same constraint will placed only on CustSat and OnTime in the Plant Model.

3. The Final Model

The two final pieces of the model formulation are now in place. The models are both constant returns to scale models that utilize total hours scaled by risk factor as an input, all six outputs measures, with constraints on the un - correlated parameters restricting their weight to less than 50% of each overall efficiency score. Analysis of the efficiency scores and an examination of improvement methods for inefficient offices can now be examined.

B. EFFICIENCY SCORE SUMMARY

1. Overview Of Results

Efficiency scores for all offices are at Appendix A. The results of each model are summarized in the following tables and figures.

	Area	Plant
Number Efficient	7	8
Mean	74.71%	66.58%
Median	72.07%	69.99%
Standard Deviation	21.46%	27.30%
Range	80.67%	99.38%
Minimum	19.32%	0.61%
Maximum	100%	100%

Table 5. Summary Statistics

Examination of the summary scores leads one to assume that the model results were quite similar. However, closer inspection of score frequency diagrams tells a different story. While most of the Area Model's offices have scores above 50%, the Plant Model has a significant amount of low scoring offices.

Stem: Tens, Leaf: Ones

0							
1	9						
2							
3	4						
4	7						
5	0	5	7	9			
6	0	4	5	6	7	9	
7	1	2	2	4	4	5	
8	5	9					
9	1	8	9				
10	0	0	0	0	0	0	0

Figure 10. Area Model Score Frequency Stem and Leaf Display

Stem: Tens, Leaf: Ones

0	1							
1	3	4						
2	8							
3								
4	4	5	5					
5	0	1	2	3	6	9		
6	0	1	1					
7	0	0	1	3	6	6	7	
8	3	7	9					
9								
10	0	0	0	0	0	0	0	0

Figure 11. Plant Model Score Frequency Stem and Leaf Display

Inspection of the data for these four poor performers reveals insight into their low efficiency score. While in all cases, their input hours value was near the average of all other plant offices, all four reported zero for their MUMM statistic. That is: the value of their contracts managed was zero. Because MUMM data is only collected for one kind of

contract (Systems Acquisition), this fact alone is not terribly unusual. However, closer inspection of the input data shows hours logged specifically for Systems Acquisition contracts. This leads to the assumption that a Systems Acquisition contract value greater than zero, no matter how small, should be in the MOCAS database for these offices. Additionally, their contract count statistics, while not zero, were very low compared to other offices. The lower value of the quantitative output measures for these four offices (MUMM, SupCMM, and OthCMM) coupled with the imposed constraint on the qualitative measures ensured their low score.

It seems clear that some type of data collection error is in evidence in either the PLAS or MOCAS database for these few offices. Fortunately, this does not undermine the methodology. While an artificially high measure in the data may perturb the results of the model, incorrect low scores will not. In any case, inferences about the efficiency of these four offices are difficult to ascertain.

2. Quantitative vs. Qualitative Measures

Plant and Area offices generally rely on different subsets of outputs in optimizing their efficiency scores. The Area Model consistently relied on quantitative measures to produce efficiency scores for its office. The early data analysis in Chapter II certainly showed that a significant relationship exists with these measures while the qualitative measures failed to show any correlation was present in hypothesis testing. In Figure 10, The portion of quantitative measures making up the efficiency score of each offices is plotted against the total efficiency score. (For example, the portion of an efficiency score of 75% may be made of 50% quantitative measures and 25% qualitative measures.)

Those offices lying along the "100% Dependence" line base their entire efficiency score on the quantitative measures. The farther offices lie from that line, the more they are dependant on the qualitative measures. Figure 13 shows the Area Model qualitative measures vs. their overall efficiency score. This graph is the complement or "mirror" of Figure 12. Those offices with a high dependence on qualitative measures are now nearer the 100% dependence line.

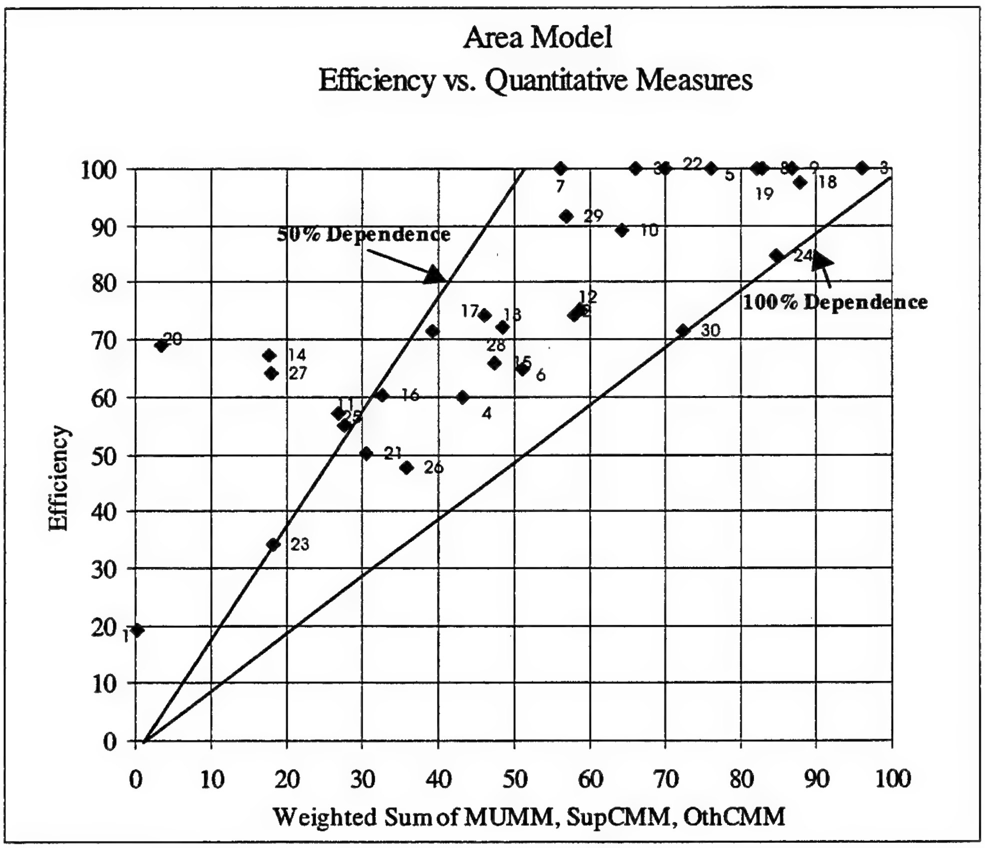

Figure 12. Area Model Efficiency Scores, Quantitative Contribution

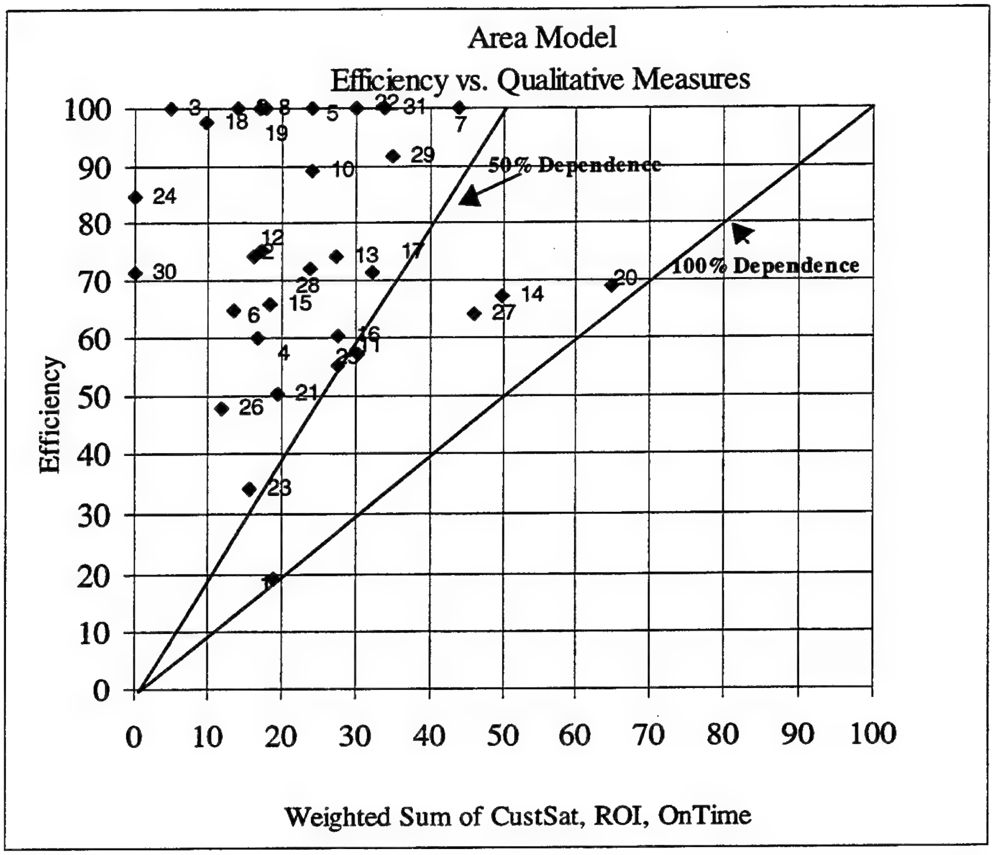

Figure 13. Area Model Efficiency Scores, Qualitative Contribution

Inspection of the same plots with the Plant Model shows that quite a different parameter combination is at work. In those offices that rely heavily on either quantitative or qualitative measures, more favor the quality type measures. However, no clear trend is admitted in the Plant Model. It seems that the Plant offices use a variety of parameter combinations to calculate efficiency scores.

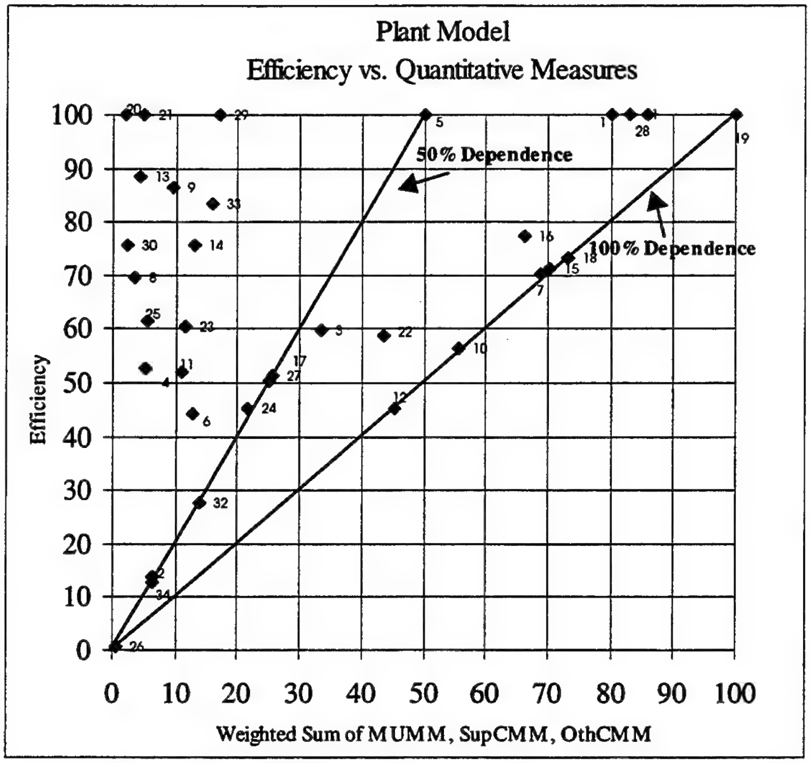

Figure 14. Plant Model Efficiency Scores, Quantitative Contribution

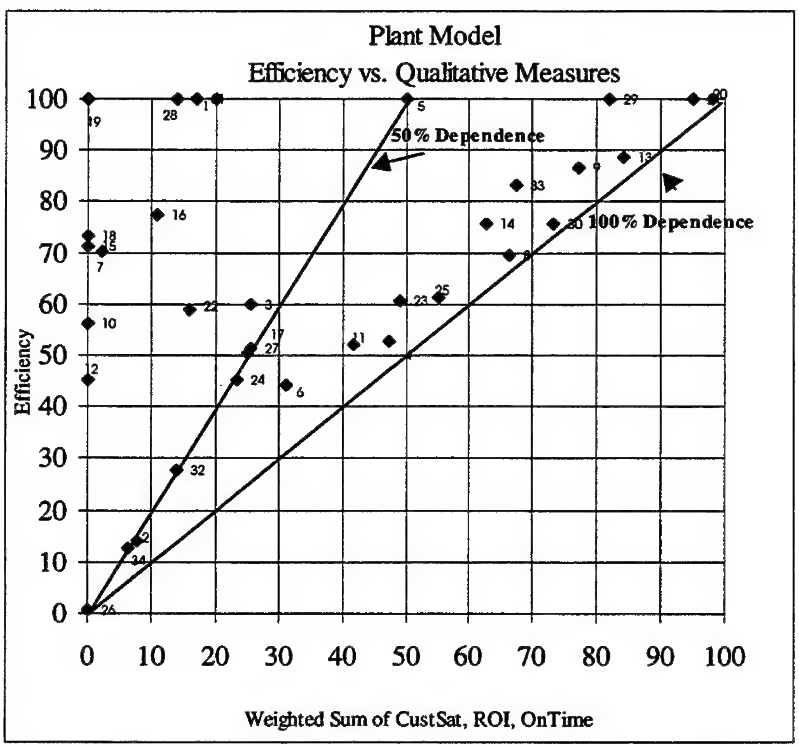

Figure 15. Plant Model Efficiency Scores, Qualitative Contribution

C. IMPROVEMENTS FOR THE INEFFICIENT

For an office to improve its efficiency score it must either reduce inputs, increase outputs, or both. By examining an inefficient office's reference set, improvement options can be identified.

1. Reference Sets

The reference set is the set of efficient units (offices) that an inefficient unit has been most directly compared with when calculating its efficiency rating. It contains the efficient units which have the most similar input and output orientation as the inefficient unit does. The reference set offices should therefore provide examples of good operating practice for it to emulate.

Area Office 29, an inefficient office, has four efficient offices in its reference set: Offices 5, 7, 9, and 31. As detailed in Table 6, each reference set office, using Office 29's optimal weights and not their own, can still achieve an efficiency score of 100%.

Office		S.Hours	CustSat	OnTime	MUMM	SupCMM	OthCMM	ROI	Score
5	**Value**	148225	5.74	52.35	3921	46289	24084	13135	
	Weight*Value	*1.19*	*0*	*21.25*	*60.88*	*0*	*11.90*	*26.40*	*100*
7	**Value**	41672	6.00	70.45	256	18819	1334	2	
	Weight*Value	*0.33*	*0*	*28.59*	*3.98*	*0*	*0.66*	*0.01*	*100*
19	**Value**	143907	5.85	61.90	5330	52008	7973	1640	
	Weight*Value	*1.15*	*0*	*25.12*	*82.75*	*0*	*3.94*	*3.30*	*100*
31	**Value**	94051	5.65	64.17	3102	15385	904	226	
	Weight*Value	*0.75*	*0*	*26.04*	*48.17*	*0*	*0.45*	*0.46*	*100*
29	**Value**	124816	5.71	74.61	3428	39586	7428	2283	
	Weight*Value	*1.00*	*0*	*30.28*	*53.22*	*0*	*3.67*	*4.59*	*91.76*

Table 6. Reference Set Comparison

Inspection of the values in the reference set allows Office 29 to compare itself with offices that operate under similar conditions. Emulating one these offices guides

Office 29 in the direction of efficiency. From the table, Office 29 is fairly consistent with offices in its reference set. Because of it already relatively high score (91.76%), no obvious poor performance in this office is readily seen. However, it is possible that a modest improvement could be made by increasing ROI to align more closely with Office 5.

An interesting result of having only one input measure for each model is the fact that by holding the current output factors constant, the efficiency score can be increased by a corresponding decrease in S.Hours. Simply put, an input level that is 91.76% of the current level would increase the efficiency score to 100%. Put another way, Area office 29 can become efficient by reducing its input hours by 8.24% or about 54 thousand hours.

2. Efficient Frontiers

By collapsing the outputs into two groups, the quantitative and qualitative, the efficient frontier can be seen in two dimensions. In Figure 16, Office 29 appears close to the frontier. Area Office 29 can increase efficiency by moving right, increasing its qualitative factors, or by moving up, increasing its quantitative factors. The most direct route to the efficient frontier is the path from the origin through point 29 onto the frontier. This direction of improvement shows the most rapid route to efficiency. However, in DCMC's case, quantitative measures are not under the control of local management. Most likely, this office can only move right to the frontier to achieve efficiency. As a comparison, the efficient frontier for the Plant model is at Figure 17.

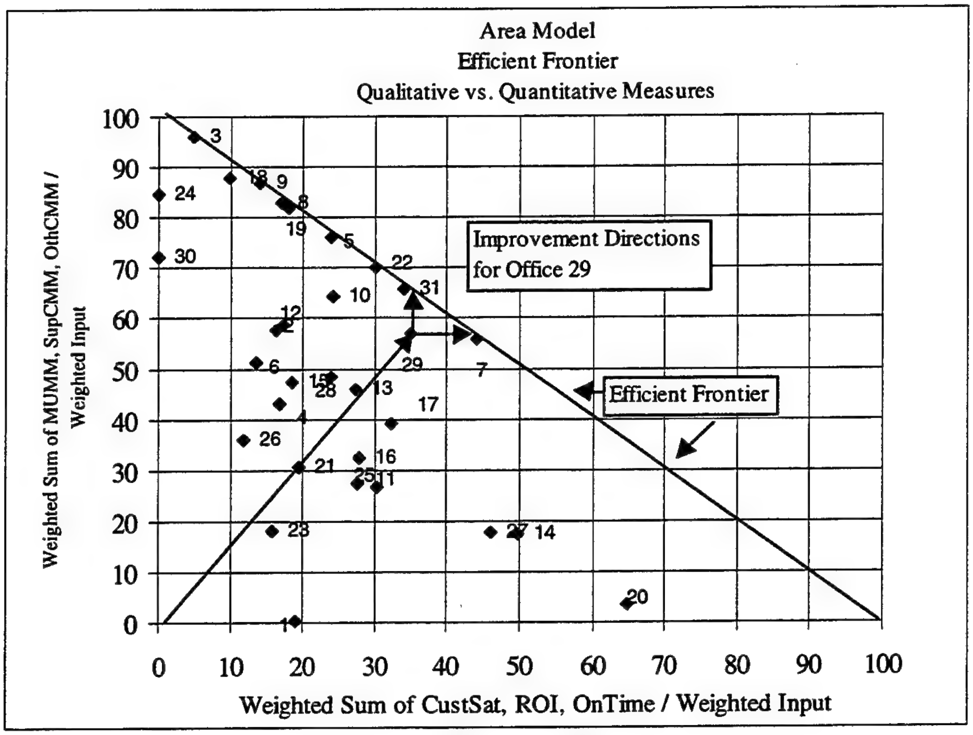

Figure 16. Area Model Efficient Frontier

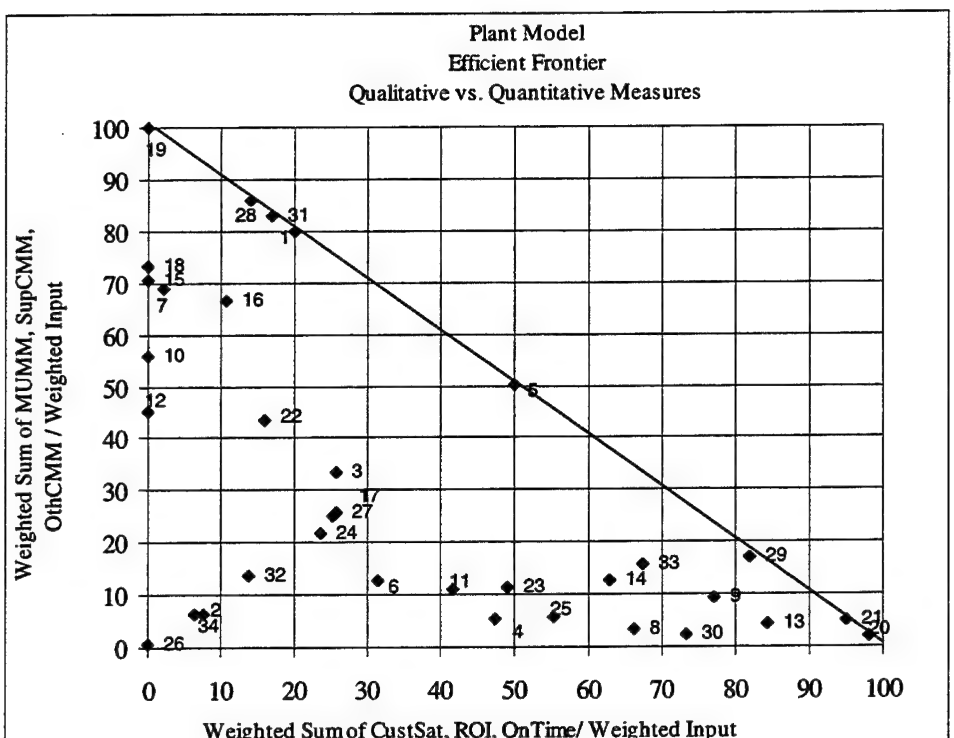

Figure 17. Plant Model Efficient Frontier

D. EFFICIENT UNITS AND OVERHEAD COST

In Chapter II, an environmental factor, overhead cost, was evaluated as a potential input or output. This measure showed the dollar value cost per hour for each office, that was not strictly related to the core tasks. These types of costs included training costs and travel time costs, among others. Unfortunately, this measure did not have the attributes to contribute to the model as either an input or output. However, overhead cost may contribute to this study by showing an overhead cost trend in efficient offices. If such a trend exists, inefficient offices, by means of comparison, can determine if their overhead costs are too small or too large. Too little overhead cost may indicate that not enough time is spent in organization-sustaining work such as training. Too much may show that staff is distracted from its core tasks of administering contracts.

Figures 18 and 19 show efficiency scores plotted with overhead costs. The plotted means (dashed lines) for both efficient offices and for all offices seem to show that efficient offices have a somewhat smaller average overhead cost associated with them. However, in the Plant Model, a level .05 Wilcoxon rank-sum test strongly rejects the null hypothesis that the efficient office mean overhead cost is the same as the mean for all offices. This suggests that in the Plant Model, efficient offices have a significantly lower than average overhead cost. Such strong evidence does not exist in the Area Model even though the average overhead cost is higher for inefficient offices. In general, an overhead cost significantly higher than the average efficient office's may be an indicator of inefficiency, although some exceptions are present.

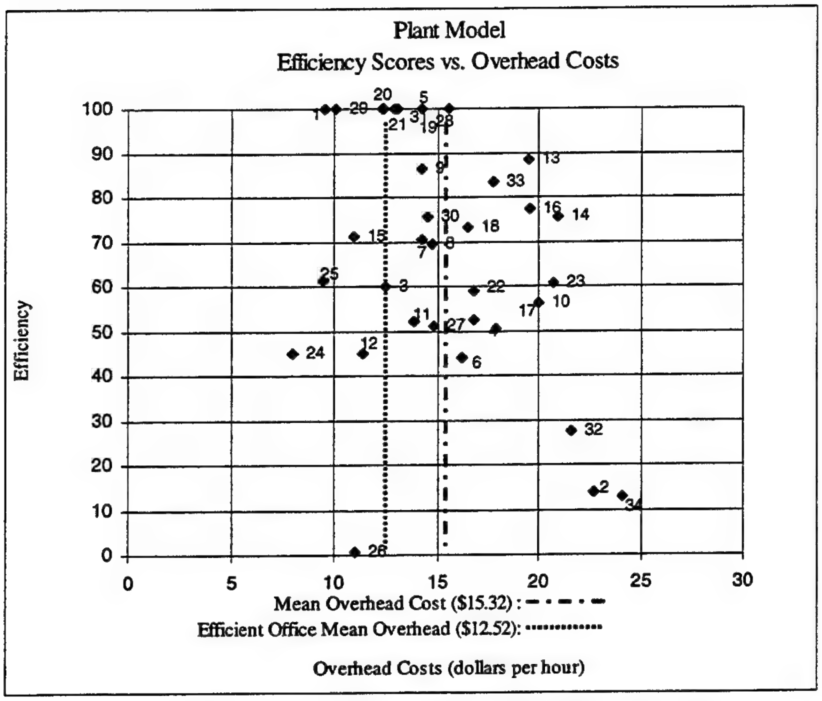

Figure 18. Plant Model Overhead Costs

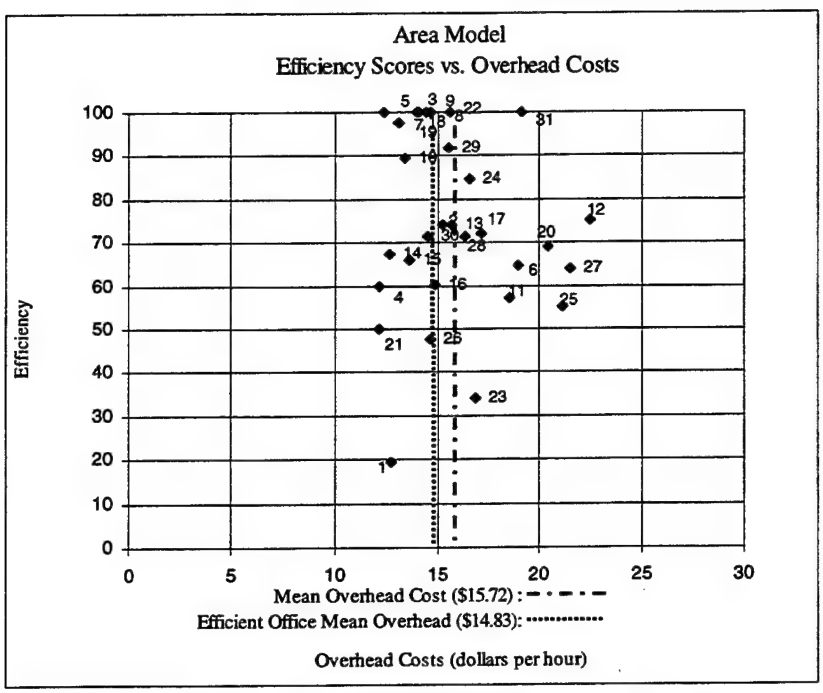

Figure 19. Area Model Overhead Costs

E. CONCLUSION

This chapter commenced with the final formulation of DEA models for DCMC. All the previous data analysis and model investigation from Chapters I through III led to a DEA model that assumes constant returns to scale but with added constraints on some variables. Constraints were imposed to limit the effect of those output parameters that displayed little or no correlation with the input parameter.

Scores were then analyzed to determine by what means inefficient offices could become efficient. Finally, by observing the overhead costs associated with each office, a trend was found to show inefficient offices yet another possible avenue to improve efficiency score. Chapter V will discuss specific recommendations for further study, as well as recommendations for DCMC should these models be implemented to assist in policy decisions.

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V. RECOMENDATIONS

One goal of this thesis is to determine the efficiency of all 65 CAOs in DCMC. Only 15 of these offices are shown to be efficient. It is important to remember, however, that each office is evaluated in the very best possible light with respect to the given model parameters. If the assumption that the six modeled outputs and one modeled input make up the vast majority of resources and products within DCMC, then the resultant DEA efficiency score is the best possible score for each office.

A. MODEL VULNERABILITY

The model in its current form is vulnerable to data manipulation by individual offices. Because some of the data elements originate within each CAO, those elements are not subject to auditing by higher level management. Especially vulnerable to internal manipulation is the ROI factor and the total Hours figure. Each are reported directly by the CAOs. While not to imply that wholesale manipulation of the data by the individual offices would arise, certainly some system of auditing those reports would be prudent. In fact, the problem with the Hours figure is easily solved. A comparison of the total Hours figure with the number of employees in each office shows these two measures to be nearly identical. Modeling with the number of employees provides nearly identical DEA efficiency scores. Hours were used in these models because DCMC believes that the PLAS database gives a more accurate view of total input.

The other measures used in the study are not generated at the CAO level and are sufficiently robust as to need no further manipulation.

B. DATA COLLECTION CONCERNS

The quality of the customer satisfaction rating is questionable due to the low report rate by serviced contractors. In order to make CustSat a higher quality measure, a concerted effort by management, which may ultimately require a new approach to customer satisfaction data collection, is certainly in order. Surely a bottom line quality measure is absolutely essential in a model such as this and customer satisfaction has potential to be that measure.

DEA literature emphasizes that a causal relationship between inputs and outputs must be present (Norman, 1991, p. 178). Because no relation between input hours and these qualitative measures is evident present, management should implement systems to reward, or at least emphasize these measures as the key quality metrics for the entire organization. Once these new policies have been established, increased correlation between the input and these measures are expected.

C. INTERPRETING THE RESULTS

The result that 50 offices of 65 in DCMC have an efficiency score less than 100% does not immediately imply that an automatic reduction in personnel strength is in order for all 50 offices. Certainly, a best approach is to examine an inefficient office's reference set, determine obvious improvement opportunities, and work to improve efficiency. Ultimately, however, some offices may indeed require staffing reduction.

Further, this study did not take into account any type of "baseline" personnel resource requirement. If we assume that every office needs a minimum number of employees to accomplish daily routine missions, regardless of the workload assigned, it is a fair argument that the DEA model should only model those hours above the baseline

figure. This baseline figure may account for the poor showing among a few small Plant Offices.

D. CONCLUSION

The DEA models presented in this study provide a valuable management tool to assist DCMC in determining personnel resource requirements. However, these models have limitations. Used in conjunction with the current system of resource forecasting (a regression model), offices with significant resource issues and problems can be quickly identified. The great added value with the DEA models is the new visibility over each office's strengths and weaknesses. The rapid identification of these weaknesses allows management to focus on problems and solve them quickly without a great time investment searching for possible causal factors.

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APPENDIX. EFFICIENCY SCORES

Each Model (Plant Office and Area Office) was solved with various formulations. The resulting scores below detail the three final formulations discussed in the text.

Model 1 uses the un-scaled input of Hours with all six outputs. No constants are placed on any output parameters.

Model 2 uses the scaled hours input (S.Hours). The outputs are identical to Model 1.

Model 3 uses the S.Hours as input and constrains the qualitative output measures (CustSat, OnTime, and ROI) to less than 50% of each efficiency score. This model was selected for further analysis.

CAO	MODEL 1	MODEL 2	MODEL 3
1	45.51	30.64	19.33
2	71.87	74.12	74.12
3	100.00	100.00	100.00
4	60.40	59.81	59.81
5	100.00	100.00	100.00
6	62.42	64.68	64.68
7	100.00	100.00	100.00
8	100.00	100.00	100.00
9	75.39	99.84	99.84
10	87.29	89.31	89.31
11	57.59	58.87	57.08
12	69.10	75.16	75.16
13	73.67	74.10	74.10
14	70.12	69.07	67.38
15	62.74	65.83	65.83
16	53.71	60.29	60.29
17	79.18	71.47	71.47
18	92.44	97.60	97.60
19	100.00	100.00	100.00
20	98.37	74.47	68.88
21	62.50	50.00	50.00
22	100.00	100.00	100.00
23	45.88	34.11	34.11
24	78.57	84.80	84.80
25	78.39	55.14	55.14
26	47.44	47.77	47.77
27	70.31	67.03	63.97
28	72.33	72.07	72.07
29	80.14	91.76	91.76
30	71.68	71.54	71.54
31	100.00	100.00	100.00

Table A-1. Area Model Efficiency Scores

CAO	Model 1	Model 2	Model 3
1	100.00	100.00	100.00
2	51.72	57.49	13.94
3	62.11	61.39	59.84
4	66.42	64.55	52.68
5	100.00	100.00	100.00
6	45.29	45.15	44.11
7	66.78	70.34	70.34
8	74.41	73.49	69.66
9	79.45	90.41	86.60
10	56.33	56.32	56.32
11	45.85	52.46	52.07
12	39.82	45.11	45.11
13	86.96	96.25	88.63
14	92.36	82.70	75.64
15	82.63	71.15	71.15
16	76.10	77.24	77.24
17	49.48	67.20	50.39
18	56.73	73.21	73.21
19	100.00	100.00	100.00
20	100.00	100.00	100.00
21	100.00	100.00	100.00
22	56.07	58.85	58.85
23	55.06	61.23	60.60
24	68.93	68.35	45.25
25	95.25	91.88	61.39
26	0.53	0.62	0.62
27	81.53	96.13	51.24
28	100.00	100.00	100.00
29	100.00	100.00	100.00
30	81.84	92.40	75.54
31	100.00	100.00	100.00
32	65.78	57.98	27.61
33	85.88	84.02	83.32
34	54.53	46.53	12.72

Table A-2. Plant Model Efficiency Scores

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